Visualizing Industrial Development Distance to Better Understand Internationalization of Spanish Companies

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Abstract. The analysis of bilateral distance between home and host countries is a key issue in the internationalization strategy of companies. As a multi-faceted concept, distance encompasses multiple dimensions, with psychic distance being one of the most critical ones for the overseas investments of firms. Among all the psychic distance stimuli that have been proposed until now, the present paper focuses on Industrial Development Distance (IDD). Together with data from both the countries and the companies, IDD is analysed by means of neural projection models based on unsupervised learning, to gain deep knowledge about the internationalization strategy of Spanish large companies. Informative projections are obtained from a real-life dataset, leading to useful conclusions and the identification of those destinations attracting large flows of investment but with a particular idiosyncrasy.

Keywords: artificial neural networks, unsupervised learning, exploratory projection, industrial development distance, internationalization.

1 Introduction and Previous Work

Managing international operations is a critical component of many companies' strategy nowadays. Understanding how the differences in the idiosyncrasies of the host countries compared to the home countries may disrupt the activities of the firms or, on the contrary, be sometimes a source of opportunities, is a critical challenge faced by those companies daring to invest abroad. This pivotal role of distance between countries is so critical that the whole domain of international management has been argued to fundamentally rely on it. As Zaheer and colleagues point out, "*essentially, international management is management of distances*" [1].

Distance has been conceptualized in recent works as a multi-faceted construct [2]. As a result, different frameworks have been proposed to account for the multiple dimensions of distance which may have an impact on firm operations overseas. Thus, [3] proposed the famous CAGE framework in which distance is disentangled in cultural, administrative, geographic and economic. [4] go beyond and propose nine dimensions to measure cross-national distance, namely: economic, financial, political, administrative, cultural, demographic, knowledge, global connectedness and geographic. In turn, these dimensions of distance have also been dissected into components or dimensions to better understand this complex phenomenon. For instance, the seminal work of [5] proposed four dimensions of cultural distance (power distance, individualisms, uncertainty avoidance, and masculinity), which were later complemented with two more (long-term orientation and indulgence) in subsequent works [6]. This framework, and its operationalization in a single construct by [7] picked up huge popularity as measured by the number of citations these works accumulate.

However, recently, the literature has started to point out that "*cultural dimensions and measures do not fully capture psychic distance, which is really the key parameter affecting many managerial choices in an international business*" [8]. Psychic distance is a broader framework encompassing cultural but also other dimensions of distance [9] [10]. Given the difficulty of assessing a manager's perceptions just at the moment of making a decision, or avoiding the causality problems due to *ex-post* perceptions being biased by the final outcome of the decision, [9] propose six macro-level factors, known as psychic distance stimuli, that shape the context in which perceptions are formed [11]. Specifically, these stimuli measure national differences in education, industrial development, language, democracy, social system, and religion that make the flow of information from and to the host market harder [9] [12]. The real relevance of these stimuli has been demonstrated in empirical studies which have showed a significant impact on performance, online internationalization, market selection, entry mode choice, trade flows, and Foreign Direct Investments (FDI) [13].

Many of these studies, however, continue the tradition of aggregating several stimuli into a single construct, despite various authors arguing that this procedure may lead to erroneously think that all the components are equally [14] [15] significant. Aware of this criticism, in this paper we focus on only one stimulus, namely Industrial Development Distance (IDD), to concentrate on the individual effects irrespective of the potential confounding effects of the other stimuli. While we acknowledge that all stimuli can have an important role, we focus on industrial development as it is arguably one of the most important factors affecting the majority of firms regardless their size, sector and experience as this indicator is calculated based on differences in GDP, the consumption of energy, vehicle ownership, employment in agriculture, the number of telephones, radios and televisions, and percentage of non-agricultural labour. As a consequence, difference in industrial development can have a critical impact on FDIs, especially those following an efficiency-seeking approach, i.e. those looking to increase efficiency and cost reduction [16].

Artificial Neural Networks have been applied to many different fields in a wide variety of systems for quite a long time [17] [18] [19] [20]. [21]. In present paper, internationalization data are visualized through three different neural projection methods. Differentiating from previous work, in present paper they are applied to internationalization data for the first time. Additionally, this paper goes one step further, enriching the visualization with IDD information to ease the analysis of the dataset.

The rest of this paper is organized as follows: the applied neural methods are described in section 2, the setup of experiments and the dataset under analysis are described in section 3, together with the results obtained and the conclusions of present study that are stated in section 4.

2 Neural Visualization

This work proposes the application of unsupervised neural models for the visualization of internationalization data. Visualization techniques are considered a viable approach to information seeking, as humans are able to recognize different features and to detect anomalies by means of visual inspection. The underlying operational assumption of the proposed approach is mainly grounded in the ability to render the high-dimensional data in a consistent yet low-dimensional representation.

This problem of identifying patterns that exist across dimensional boundaries in high dimensional datasets can be solved by changing the spatial coordinates of data. However, an a priori decision as to which parameters will reveal most patterns requires prior knowledge of unknown patterns.

Projection methods project high-dimensional data points onto a lower dimensional space in order to identify "interesting" directions in terms of any specific index or projection. Having identified the most interesting projections, the data are then projected onto a lower dimensional subspace plotted in two or three dimensions, which makes it possible to examine the structure with the naked eye.

2.1 Principal Component Analysis

Principal Component Analysis (PCA) is a well-known statistical model, introduced in [22], that describes the variation in a set of multivariate data in terms of a set of uncorrelated variables each, of which is a linear combination of the original variables.

From a geometrical point of view, this goal mainly consists of a rotation of the axes of the original coordinate system to a new set of orthogonal axes that are ordered in terms of the amount of variance of the original data they account for. PCA can be performed by means of neural models such as those described in [23] or [24]. It should be noted that even if we are able to characterize the data with a few variables, it does not follow that an interpretation will ensue.

2.2 Maximum Likelihood Hebbian Learning

Maximum Likelihood Hebbian Learning [25] is based on Exploration Projection Pursuit (EPP). The statistical method of EPP was designed for solving the complex problem of identifying structure in high dimensional data by projecting it onto a lower dimensional subspace in which its structure is searched for by eye. To that end, an “index” must be defined to measure the varying degrees of interest associated with each projection. Subsequently, the data is transformed by maximizing the index and the associated interest.

MLHL is a family of learning rules that is based on maximizing the likelihood of the residual from a negative feedback network whenever such residuals are deemed to come from a distribution in the exponential family. The main advantage of this model is that by maximizing the likelihood of the residual with respect to the actual distribution, we are matching the learning rule to the probability density function of the residual by applying different values of the p parameter specified in the learning rule.

2.3 Cooperative Maximum Likelihood Hebbian Learning

The Cooperative MLHL (CMLHL) model [26] extends the MLHL model, by adding lateral connections between neurons in the output layer of the model. These lateral connections are derived from the Rectified Gaussian Distribution (RGD) [27], that is a modification of the standard Gaussian distribution in which the variables are constrained to be non-negative, enabling the use of non-convex energy functions. In a more precise way, CMLHL includes lateral connections based on the mode of the cooperative distribution that is closely spaced along a nonlinear continuous manifold. By including these lateral connections, the resulting network can find the independent factors of a dataset in a way that captures some type of global ordering in the dataset.

Considering an *N*-dimensional input vector (*x*), and an *M*-dimensional output vector (*y*), with W_{ij} being the weight (linking input *j* to output *i*), then CMLHL can be expressed as defined in equations 1-4.

1. Feed-forward step:

$$y_i = \sum_{j=1}^{\mathbf{N}} W_{ij} x_j, \forall i \tag{1}$$

2. Lateral activation passing:

$$y_i(t+1) = \left[y_i(t) + \tau(b - Ay)\right]^+ \tag{2}$$

3. Feedback step:

$$e_j = x_j - \sum_{i=1}^{M} W_{ij} y_i, \forall j \tag{3}$$

4. Weight change:

$$\Delta W_{ij} = \eta . y_i . sign(e_j) | e_j |^{p-1} \tag{4}$$

Where: η is the learning rate, τ is the “strength” of the lateral connections, b the bias parameter, p a parameter related to the energy function and A a symmetric matrix used to modify the response to the data. The effect of this matrix is based on the relation between the distances separating the output neurons.

3 Experiments & Results

As previously mentioned, some neural visualization models (see Section 2) have been applied to visualize IDD on a dataset gathering information about internationalization. Present section introduces the analyzed dataset as well as the main obtained results.

3.1 Dataset

The dataset analysed in present study is based on a sample of all Spanish MNEs registered with the Foreign Trade Institute (ICEX) and from the website www.oficinas-comerciales.es, both managed by the Spanish Ministry of Industry, Tourism, and Trade. In order to analyze a representative sample of companies with sufficient autonomy, we restricted the sample to keep only those large and independent enough to conduct and decide their own internationalization strategy. Thus, following a well-established cut-off point in International Business literature, we dropped from the sample those with less than 250 employees. We also dropped those companies with a foreign majority owner controlling more than half of the capital.

It is also important to note the huge impact of the financial crisis on the Spanish economy, which forced many multinational enterprises to sell or postpone international operations in order to focus on the problems of the home market. To avoid distortions in the results due to this exogenous effect, we took the year 2007 as our base year. Overall, the sample consists of 164 companies investing in 119 countries worldwide. Unfortunately, Afghanistan, Andorra, Puerto Rico, and São Tomé and Príncipe are not included in the sample due to a lack of data. In addition, Serbia, Montenegro, and Kosovo are included as a group because at the time of the study they constituted a single country.

For the companies and countries above mentioned, the following data about each one of the cases of international presence were collected (further details about the different features can be found in [13]):

- Company sector: 5 binary features stating the economy sector the company belongs to (manufacturing, food, construction, regulated and others).
- Company product diversification: 3 binary featuring (non-diversified, related or unrelated diversification).
- Other company characteristics: Assets, number of employees, Return on Assets (ROA), ROA growth, age, number of countries where the company operates, leverage and whether or not the company is included in a stock market.
- Host country characteristics: GDP, GDP growth, total inward FDI, population, unemployment, level of corruption and Economic Freedom Index.
- Geographic and psychic distance stimuli between home and hot countries [9]. The education distance stimulus is based on differences on literacy rate and enrolment in second and third-level education. The industrial development stimulus takes into account differences in ten dimensions such as in energy consumption, vehicle ownership, employment in agriculture, number of telephones and televisions, etc. The language stimulus is based on the differences between the dominant languages and the

bilateral influence of each country's major language in the other country. The democracy stimulus includes differences in political rights, civil liberties and POLCON and POLITY IV indices. The political ideology stimulus is based on the ideological leanings of the chief executive's political party and the largest political party in the government. Finally, the religion stimulus is calculated based on the differences between the dominant religions and the bilateral influence of each country's dominant religion in the other country.

As a result, a dataset containing 1456 samples and 33 features was obtained and the obtained projections are presented in the following subsection.

3.2 Results

For comparison purposes, three different projection models have been applied, whose results are shown below. In all of them, the IDD has been added to the projection by means of the glyph metaphor. In order to do that, every sample (international presence) is depicted in a certain way, according to the quartile of the original IDD value: * 1st quartile, O 2nd quartile, ▷ 3rd quartile, and + 4th quartile.

PCA Projection

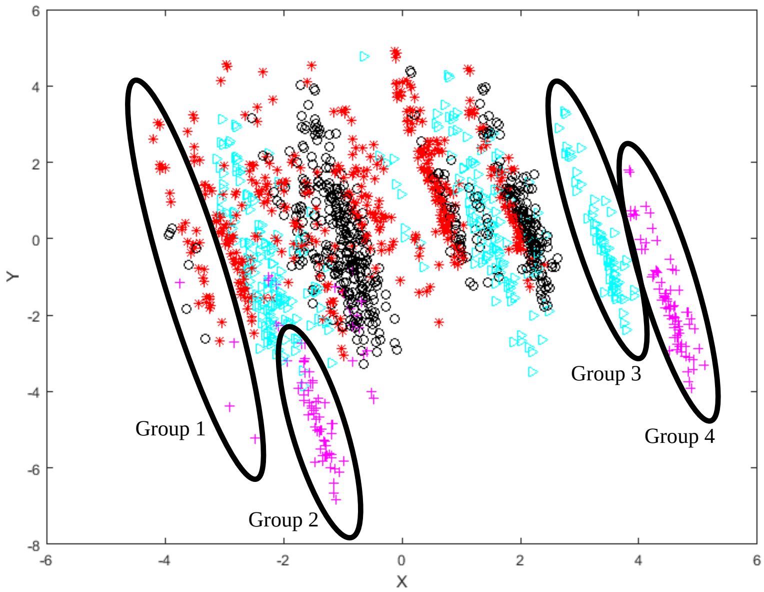

Fig. 1. PCA projection of the dataset, visualizing IDD.

Fig. 1 shows the principal component projection, obtained by applying PCA to the previously described data, and combining the two principal components. It can be seen that data are split in several different groups; some of them are labeled (1-4).

A thorough analysis of the most representative groups of PCA projection has been carried out. As a result, it can be said that most samples with highest values of IDD are placed in groups 2 and 4, at the bottom of the projection. The samples that are closest to these two groups are all of them from the 2nd quartile of IDD. Group 1 comprises investments in under-developed countries such as Venezuela, Bangladesh and Nigeria. Group 2 is entirely made of all investments in China. While this country has become one of the top recipients of FDI in the world due to its emerging economy, its particular idiosyncrasy makes it a distinct group and the large IDD value differentiates it from the other groups. Group 3 is also entirely made of all investments in one country, in this case UK. While being one of the top destinations for Spanish FDI flows, this country is singled out due to its significant differences compared to the rest of main destinations in the EU. Finally, Group 4 comprises all investments in the US. As the largest economy of the word, this country started to be a main destination for Spanish FDI flows since the beginning of the 21st century [28], but, it also exhibits the largest IDD score as it appears to be perceived as much more advanced.

MLHL Projection

Fig. 2 shows the IDD-enriched projection on the two main components identified by MLHL from the analyzed data. The parameter values of the MLHL model for the projection shown in Fig. 2 are: number of output dimensions: 3, number of iterations: 3000, learning rate: 0. 08009, p: 0.54.

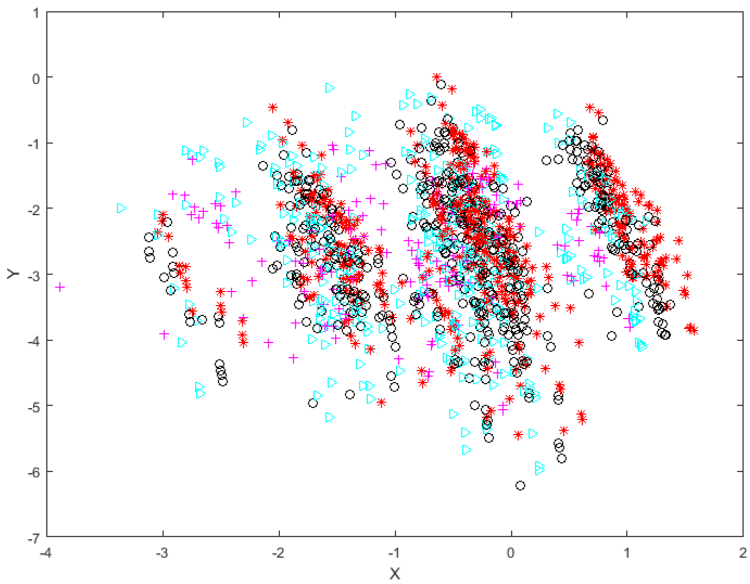

Fig. 2. MLHL projection of the dataset, visualizing IDD.

As the MLHL projection does not reveal a clear organization of samples according to IDD, and for the sake of brevity, this projection is not further studied in present paper.

CMLHL Projection

When applying CMLHL to the analysed dataset, the projection (on the two main components) shown in Fig. 3 has been obtained and IDD information has been added. The parameter values of the CMLHL model for the projections shown in Fig. 3 are; number of output dimensions: 3, number of iterations: 3000, learning rate: 0.000175, p: 1.96, τ: 0.034.

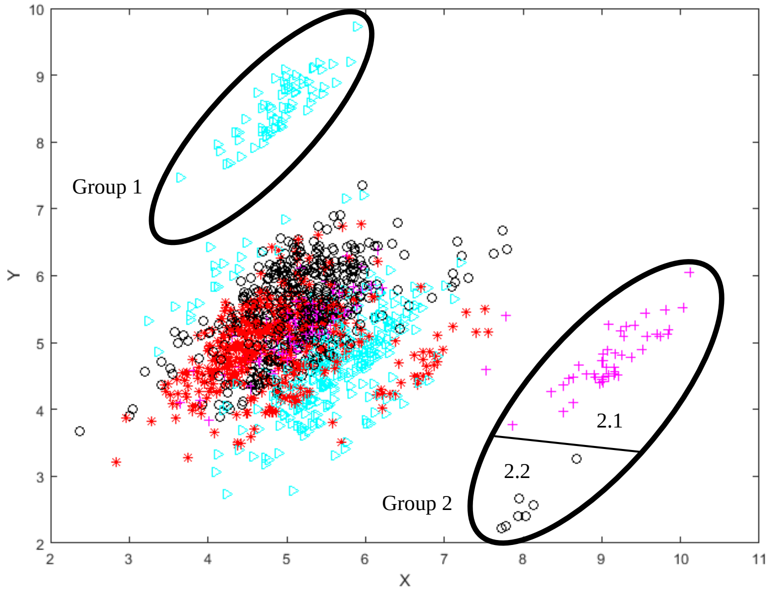

Fig. 3. CMLHL projection of the dataset, visualizing IDD.

In Fig 3 it is easy to visually identify some groups of data; the most distant ones are labeled as 1 and 2. Group 1 displays all investments in UK, as the previously described Group 3 in the PCA projection. Group 2.1 gathers all investments in China, as the previously described Group 2 in the PCA. Finally, Group 2.2 displays all investments in Serbia, Montenegro, and Kosovo. This group may be unexpected, especially since the companies investing in this country are quite heterogeneous (infrastructures, shoes, clothing, …). While we can speculate maybe it can be due to the specific situation previous to the split of this territory into multiple countries short after, further research is needed to disentangle this finding.

4 Conclusions and Future Work

From the projections in section 3, it can be concluded that neural projection models are an interesting proposal to visually analyse internationalization data in order to better understand it. More specifically, when visualizing IDD, neural projections let us gain deep knowledge about the nature of such dataset.

After the analysis of the projections and the associated allocation of international presence, it can be said that these techniques are useful to identify those destinations attracting a large share of subsidiaries from multinational enterprises but at the same time exhibiting a distinct environment (e.g., China, UK, US) compared to other more homogenous regions where Spanish FDI is also prominent (e.g., UE, Latin America).

This finer-grained analysis would allow firms to obtain a more nuanced understanding on the specific characteristics and idiosyncrasies of the foreign markets where they are currently conducting operations as well as other potential host markets where they might be considering as potential destinations for investment. By signaling those host countries exhibiting some particular differences compared to other alternative destinations, managers will be able to make better location-decision choices and will be more aware of the need to get familiarized with the specificities of the local market.

In future work, some other neural visualization models will be applied to the same dataset to better understand its nature and gaining deep knowledge of the internationalization strategy of Spanish companies.

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